A new multi criteria classification approach in a multi agent system applied to SEEG analysis.

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Abstract—**This work is focused on the study of the organization of the SEEG signals during epileptic seizures with multi-agent system approach. This approach is based on cooperative mechanisms of auto-organization at the micro level and of emergence of a global function at the macro level. In order to evaluate this approach we propose a distributed collaborative approach for the classification of the interesting signals. This new multi-criteria classification method is able to provide a relevant brain area structures organisation and to bring out epileptogenic networks elements. The method is compared to another classification approach a fuzzy classification and gives better results when applied to SEEG signals.**

I. INTRODUCTION

Epilepsy is a chronic disease, a consequence of many and various causes. Each epilepsy is particular case according to its cause, the age at which appeared the seizure, their frequency, their intensity, their sensitivity to the treatment or external events (luminous flash, noise) and their evolution. According to the nature of the phenomena arising at the brain level, their propagation mode and their duration, can take various forms. In others words, one type of epilepsy does not exist, but many epilepsies. It is a complex pathology which the symptoms ("clinical signs") exteriorized by the patient depend directly on the brain structures involved in the propagation of the seizure [1].

Stereo electroencephalography (EEG recorded by depth electrodes) is the means of investigation used here to obtain physiological SEEG signals type and recorded on several channels. This paper deals with this type of signals (figure 1). The methods of investigations used in epilepsy make it possible to better include/understand the mechanisms which are responsible of the initiation of the paroxystic discharges in a given subset of cerebral structures and their propagation to other structures. The SEEG signals recorded, present sharp variations of their statistics on all or part of the channels illustrating the various cerebral activities (figure 1).

The knowledge of these channels and the moments of variations can allow the description of the privileged channels of propagations corresponding to the contamination of others cerebral structures by the initiating paroxystic hearth.

We propose in this work a distributed collaborative approach for the classification of the interesting signals. The problem is approached here by a multi-agents system (MAS) based on cooperative mechanisms of auto-organization at the micro level and of emergence of a global function at the macro level.

Paragraph 2 presents the general context of our work and the problem addressed. The third paragraph deals with the new classification method proposed. The fuzzy classification algorithm is present in paragraph 4. Results are commented in paragraph 5 and the last part of this work gives some conclusions elements.

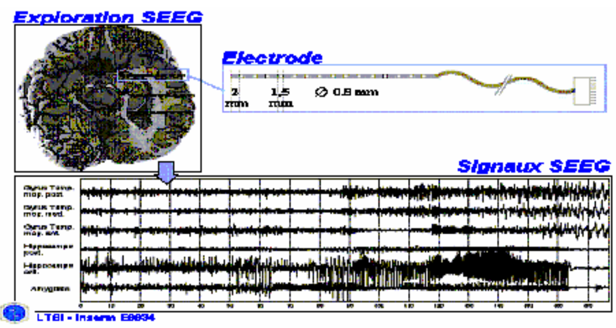

Fig.1 Example of SEEG signal

II. CONTEXT: MULTI AGENT SYSTEM AND SEEG SIGNALS

The MAS technical are often used in the field of the artificial intelligence, the distributed information processing systems and the software genius. This discipline is interested in the collective behaviours produced by interactions of several autonomous and flexible entities called agents. These interactions are named the co-operation, the competition and the coexistence between these agents. The multi agent systems and signal processing applying to epilepsy are two very distant fields in the literature; however a close links can exist between these two fields by the entities which compose them.

- First (SMA) results from data processing and the co-operative distributed artificial intelligence. Then the second comes from the observation, the study of cognitive neuroscience and the cerebral activity.

- The multi agent systems can allow modelling and simulation of aggregates of neurons or systems based on autonomous entities, with distributed interactions.

These two remarks build the common interests to study the association of these two research fields.

Scalar analysis of the epileptic signal by the measurement of relation between signals [1] highlighted the existence of mutual interactions between the SEEGs. In the same way the epileptogenic network's concept developed by Professor Patrick CHAUVEL [2] gives raise to the existence of a co-operation between cerebrals areas in epileptic processes.

This work aims to take part thanks to the distributed technical (multi-agent concept), to the description of the networks concepts which suppose "regrouping of the interesting signals".

Our approach is built starting from several groups of agents whose properties and missions must allow:

- to classify the signals with the same activities and/or contained the same spectral (groups).
- to classify the signals whose activities change at the same time (segmentation)(groups)
- to represent the seizure by an image which gives a time and space representation of SEEG signals with the same pathological or similar activities
- to associate all these partial results in order to achieve a global behaviour of the analyzed seizure .

The present work is focussed on the first two points. It aims to provide the best classifier of SEEG signals belonging to different cerebral areas in order to suitable compute the MAS approach.

In practice, the signal agents represent the executive component of the system as presented in our previous work [3]. They are charged with carrying out the signal processing tasks on behalf of the structural agents. They are equipped with particular qualities allowing them to quantify and to analyze the information coming from SEEG sensors following different strategies. They provide quantitative information: a scalar grading, a characteristic vector of the associate signal and degrees of links with other agents [3]. This approach, based on a multi- agent system (MAS), therefore incorporates different criteria (similarity, statistical relations and synchronization measures) so as to enable the problem to be solved better and to interpret the electrophysiological signals (non -stationary, non- linear, combined problem, lack of global methods, etc.). The evaluation of all possible combinations on N channel (N>100) is practically impossible in a reasonable time. Hence, the necessity of selection strategies to compute the interesting signals. Each signal agent Asi disposes of three lists local data "**local Group**", "**uncertain**" and "**localOutGroup"** where it registers respectively the list of agents which have properties similar to its own and the list of agents whose properties are different to its own. To do that the signal agent fixes thresholds η_s of detection of certain similarity (sure) and a tolerance level η_d above the level of detection in order to fill up its two bases of local data. We consider for the following that each signal agent assimilates the entities of the base "local Group" as attractions and the entities of the base "local out Group "as repulsions (figure2).

The selection of interesting agents results in three behavior of the signal agent meeting-diffusion-decimation [3]. It relies on the classification of interesting signals. This classification results in the necessity to regroup similar signal agents in the same cerebral region. The reasons for this regrouping are firstly a strong probability that similar elements in the same structure (localization) are carriers of the same information. Secondly the regrouping allows a global solution to emerge without carrying out all possible operations (an important stage in reaching the final objective.) The global objective of the system is the carrying out of signal processing tasks (on the totality of the SEEG exploration) under the constraint of a limited work capacity. The MAS is use to limit the quantity of data to be exploited, it can give interpretation elements as close as possible to an exhaustive analysis which will exploit the totality of data issuing from the SEEG exploration [4][5].

III. COLLABORATIVE CLASSIFICATION

The classification of similar agents is based on two thresholds fixed by the system user and the prior information on the rules of attraction and repulsion. The first threshold η_s assures the signal agents the detection of certain similarity and the second threshold η_d fixes an interval of uncertainty above the threshold η_s where the agents will have to adopt a cooperative behavior. The problem of thresholds is that it is often too high to accept the uncertain similarities and sometimes too weak to reject the similarities which should be accepted. The solution proposed by the system is to minimize the decision threshold and to introduce an interval of uncertainty fixed by the cooperation between the system agents. The signal agents dispose of prior information clear about the acceptance or rejection in certain situations (similarities or obvious differences) but must rely on other system agents and the information which they receive from the latter in order to decide to unite or separate from other signal agents. The signal agent also has recourse to a cooperative behavior to take a decision concerning the intermediate values between the acceptance threshold and the rejection threshold. The less the prior information is precise, the more the signal agents find themselves confronted with uncertain situations. To overcome these uncertainties, the signal agents gather the supplementary information by means of the cooperative behavior of diffusion. They rely on the information of their affinities to overcome uncertain situations.

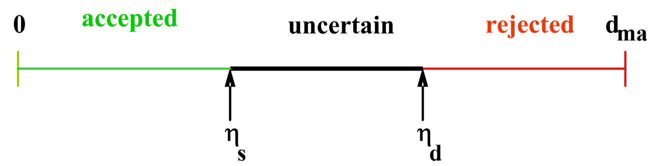

Fig. 2. The two thresholds of detection of similarities between agents. If $d(A_{si}, A_{sj}) \in [0-\eta_s]$ A_{si} and A_{sj} are very similar, if $d(A_{si}, A_{sj}) \in [\eta_d-d_{max}]$ A_{si} and A_{sj} are very different and when $d(A_{si}, A_{sj}) \in [\eta_s-\eta_d]$ A_{si} and A_{sj} should exchange their local data bases to take a decision about their similarity

Each agent disposes of three lists (localGroup, uncertainty and localOutGroup) in which the other signal agents will be classified according to the distance calculated or received from another agent.

localOutGroup is a list in which the agent inserts its neighbors with which it is not going to form an homogenous group.

uncertain is a list in which it will place its contacts which it doesn't know if it is going to accept or reject . This ambiguity will be raised with the help of the cooperative behavior of diffusion

localGroup contains contacts with which it wishes to form an homogeneous group.

This method decentralizes the classification by cooperation between the various agents in the evaluation of the distances measures between characteristic vectors. Each signal agent informs all its neighbours of the same partition about its properties and estimates the euclidian distance between its characteristic vector and that of the other one when it receives the characteristic vector of other agents. According to the value of the estimated distance, each signal agent A_{S_i} decides: *i)* to integrate A_{S_j} into its local group, *ii)* to refuse to belong in a group where is subscriber A_{S_j} or *iii)* not to pronounce for the moment on its links with A_{S_j}.

Thus, the filling up of these the two local bases necessitates for each agent a collaboration with different protagonists according to the rules:**"** *I accept in my" LocalGroup" every agent similar to one of my attractions if it is not already registered in my repulsions ("localOutGroup")" and "I refuse to join a group where one of my repulsions is registered".*

IV. FUZZY CLASSIFICATION

Fuzzy classification algorithm is based on the optimization of a quadratic criterion where each agent is represented by its gravity center (here the characteristic vectors). The algorithm is supervised; it requires the initial knowledge of the classes's number. It generates the classes through an iterative process by minimizing an objective function. Thus, a partition of the signal agents is obtained by giving each of them one degree of membership in a given class. These classes were defined from different epileptic activity most commonly encountered (background activity, tonic activity, clonic etc.). These apprenticeship classes which are not exhaustive have been constructed from SEEG recordings from several patients. They allow signal agents to associate with each of these activities contained in their signal with their nearest class.

The values of the degrees of membership are grouped together in the matrix $U = [u_{ik}]$ for $1 \le i \le M$, $1 \le k \le n_c$, where u_{ik} indicates the degree of membership of the signal $S_i(t)$ in the class C_k and n_c the number of classes. The algorithm imposes on the elements of U the constraints given below

$$u_{ij} \in [0,1] \forall i, j; \sum_{k=1}^{n_c} u_{ik} = 1 \ \forall i; \ 0 < \sum_{i=1}^{n} u_{ij} < M \ \forall M;$$

A signal agent can, according to the degree of membership in a class, be situated between several classes.

The algorithm computed the matrix U by minimizing the function of the equation $F_m(U, C)$ so as :

$$F_m(U,C) = \sum_{i=1}^{n} \sum_{k}^{n_c} (u_{ik})^m * \left\| \Gamma_{S_i} - \Gamma_{S_{c_k}} \right\|^2, 1 < m < \infty$$

Where m is a control parameter and $\Gamma_{S_{c_k}}$ is the C_k class center

V. RESULTS

The SEEG data used in this study were recorded from 5 patients (P1 to P5) suffering from a temporal lobe epilepsy and they are candidates for surgical treatment. The SEEG signals are recorded by means of deep electrodes. The recordings are made in repository mode with regard to a reference without particular filtering. The busy band is included between 0 and 128 Hz with a corresponding sampling frequency of 256 Hz. The two classification methods were computed on these SEEG signals.

A comparison of these two methods shows that the proposed method (collaborative classification) is good alternative amongst different classification methods [3][6]. The method shows the advantage of being unsupervised; it is composed of a collaborative and distributive approach and its results satisfy furthermore the clinician. In fact more than 95% of classes supplied by this method have been judged to be correct by the clinician In figure 3 we present the time frequency components of 10 SEEG signals that were classify by the collaborative classification approach.
The second method has been limited by the calculation time, however the approach is robust and very realistic method for a small dimension of the characteristic vector. The fuzzy classification algorithm converges rapidly but convergence

time increases exponentially and because of the centralized classification this method has an avidity memory.

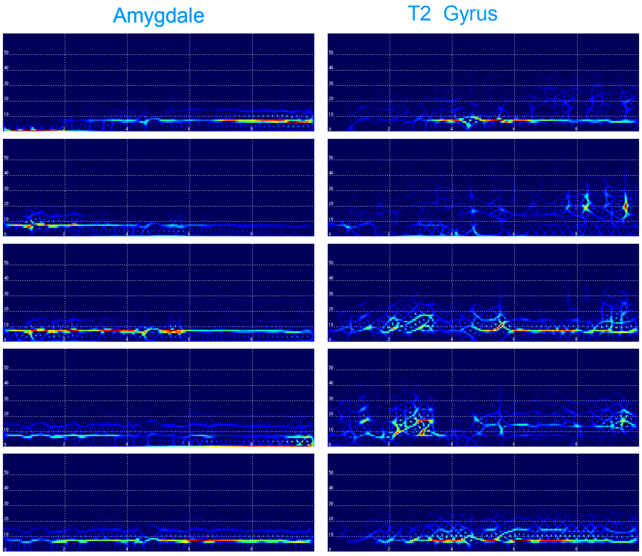

Fig.3. Proof of similarities through a time-frequency analysis amongst the properties of two SEEG brain structures explored by electrode A (collaborative classification approach).

VI. CONCLUSION AND PERSPECTIVES

We presented a new multi criteria classification approach in multi agent system. This method is compared to a fuzzy supervised classification method. Our first results show that the new and original method (collaborative classification) which is an unsupervised classification, a distributed classification seem to be a robust and realistic approach to classify interesting SEEG signals. This classification results is then include in a global multi-agent dynamic system in order to quantify interactions between brain areas when applied to temporal lobe epilepsy. As far as future works are concerned we applied this classification in a large number of seizure (about 15) and results show that the MAS approach is a good alternative to bring out pertinent SEEG characteristics and so is able to provide a relevant brain area structures organisation and one can learn about epileptogenic networks elements.

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